Optimal stock control and procurement by reusing of obsolescences in manufacturing

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Abstract: Production, procurement planning and logistic organization are complex tasks in companies with multiple production/stocking sites. For companies operating in fashion markets, these tasks are harder due to the high demand variability and frequent turnover of trends that make products outmoded rapidly.
In the field of industry informatics under an Industry 4.0 scenario, this paper presents a data and processing framework that mix a Decision Support System (DSS) and an Integer Linear Programming (ILP) model to maximize the potential revenue of the outmoded products. The solution proposed considers both the investment for missing components and the transportation costs between hubs and takes into account constraints on the overall number of items produced, the budget for new component orders and the minimum lot scheduling thresholds. Moreover, to avoid the increment of obsolescences due to raw material orders, the ILP model bounds purchased components to a percentage of used ones.
A real worldwide dataset provided by a fashion company, market leader in the design, manufacture and distribution of fashion, luxury, sports and performance eyewear, was used to test performances and repeatability of the mathematical model under different configurations. The results obtained show a huge positive impact on the financial results.

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Authors: Emanuele Frontoni, Fabrizio Marinelli, Roberto Rosetti and Primo Zingaretti

Dear Editor,

Companies operating in fashion markets usually adopt production models that are mostly demand-push oriented. Although the pull model is inherently better suited to meet the customer needs and allows better reactions to changes in customer tastes and expectations, the push model requires a smaller technological effort, is less expensive and can target sales if properly proposed to the market. Albeit proposing products to markets aims to reduce the costs of manufacturing technology and process management, the high turnover of trends, typical of the fashion markets, rapidly makes stocked parts obsolete or even useless, with significant losses for the production companies. Obsolete components can be reallocated to produce items that will be sold at a lower price on parallel markets - such as outlets and second markets - at the cost of purchase the missing components that are required to complete the bill-of-material (BOM) of out of fashion products.

In this work, we propose a framework that combines a Decision Support System and an Integer Linear Program to maximize the potential revenue of outmoded products. The mathematical formulation finds the best trade-off between the purchasing cost of missing parts and the profits of parallel markets selling. Moreover, components transfer and production load among plants are considered to maximize the total revenue. The formulation considers constraints on the overall number of produced items, budget for new component orders and minimum lot scheduling thresholds. The whole framework has been designed and tested to support dimensions and needs of Luxottica, a leading fashion company. In particular, the mathematical model has been tested under different configurations and with real worldwide data provided by this company.

As you probably know, Luxottica is a market leader in the design, manufacture and distribution of fashion, luxury and sports eyewear. Its portfolio includes proprietary brands such as Ray-Ban, Oakley, Vogue Eyewear, Persol, Oliver Peoples and Alain Mikli, as well as licensed brands including Giorgio Armani, Burberry, Bulgari, Chanel, Coach, Dolce&Gabbana, Michael Kors, Prada, Ralph Lauren, Tiffany & Co. and Versace. The Group's global wholesale distribution network covers more than 150 countries and is complemented by an extensive retail network of over 7,200 stores, with LensCrafters and Pearle Vision in North America, OPSM and LensCrafters in Asia-Pacific, GMO in Latin America and Sunglass Hut worldwide. In 2015, Luxottica posted net sales of approximately Euro 9 billion and approximately 79,000 employees.

Results are related to a project developed together with Luxottica Global Procurement Office. We have a formal approval for the submitted version of the paper and we can talk about the project in this cover letter but we cannot mention officially the brand Luxottica in the paper.

Results of the proposed methods are novel in terms of

i) theoretical approach to this application and proposed model
ii) huge economic impact on a global company operating in 150 different countries
iii) integration schema and results on one of the most complex real world scenario available in the fashion market

Thanks for considering our paper for publication on Computers & Industrial Engineering.

Best regards,

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Keywords:

Production planning; Distributed production system; Obsolete component reusing; Decision Support System; Integer Linear Programming; Fashion Industry

Title:

Optimal stock control and procurement through remanufactured products

Highlights:

- Stock control, procurement and obsolete component reusing in distributed production systems

- A modern software architecture (ETL, OR, Repository, Dashboard, DSS) to maximize results

- Tests performed on a real worldwide dataset with different configurations

- Huge positive impact on the financial outcome of the company

Optimal stock control and procurement through remanufactured products

Abstract

Production, procurement planning and logistic organization are complex tasks in companies with multiple production/stocking sites. For companies operating in fashion markets, these tasks are harder due to the high demand variability and frequent turnover of trends that make products outmoded rapidly. In the field of industry informatics under an Industry 4.0 scenario, this paper presents a data and processing framework that mix a Decision Support System (DSS) and an Integer Linear Programming (ILP) model to maximize the potential revenue of the outmoded products. The solution proposed considers both the investment for missing components and the transportation costs between hubs and takes into account constraints on the overall number of items produced, the budget for new component orders and the minimum lot scheduling thresholds. Moreover, to avoid the increment of obsolescences due to raw material orders, the ILP model bounds purchased components to a percentage of used ones. A real worldwide dataset provided by a fashion company, market leader in the design, manufacture and distribution of fashion, luxury, sports and performance eyewear, was used to test performances and repeatability of the mathematical model under different configurations. The results obtained show a huge positive impact on the financial results.

Keywords: Production planning, Distributed production system, Obsolete component reusing, Decision Support System, Integer Linear Programming, Fashion Industry

1. Introduction

Fashion oriented trading markets lead and govern style tendencies, apparel trends and all related products affecting the wearing industry. Fashion markets are not only related to cloths and shoes, but a considerable market share regards the fashion accessories like bags, jewellery, hats, sunglasses, etc. In particular, eyewears are some of those fashion products that better combine the engineered side with the stylish side of an industrial product ([1]). Despite appearances, this kind of accessory can have more than 20 different components in its bill-of-material (BOM), making it a small and complex engineering product. Eyewear market is inside a "fast" industry with high demand variability and frequent turnover of trends that makes products outmoded rapidly.

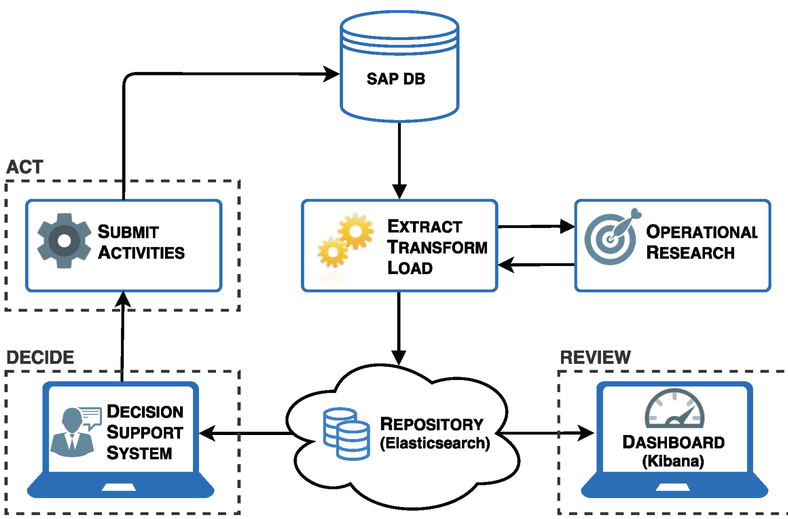

Figure 1: Integration of the "Operational Research" module within the data processing workflow.

Despite the efforts to forecast production and procurement phases, other factors, like delays in suppliers' deliveries ([2]) and human errors in procurement management, can overfill the company's warehouses of components and raw materials that remain unused. A no longer fashionable product, in fact, drags a set of components with it, making these ones no more useful for mainstream production. Components related to a discontinued product are called obsolescences. The reusing of this obsolete components can be implemented planning the production of outmoded items for parallel markets, such as outlets and second markets, where the products will be sold at a lower price.

This work proposes a framework of 'Data Intelligence' that aims to combine the production, procurement and logistics departments of a company. In a preliminary work of the authors [anonymous reference], to find the best production and procurement planning in order to maximize the financial revenues, only the stocked components and the BOMs of the finished products had been taken in consideration. This paper considerably expands that work, taking into account the competitive prices of suppliers, the costs of materials handling (transport network) and above all introducing a DSS that allows managers to choose solutions and simulate their impact before implementing the activities.

This project has been developed under the influence of *Industry 4.0* guidelines with seamless integration of the new "Operational Research" (OR) module with the existing framework. Figure 1 represents a simplified scheme of the company's workflow. On a big data architecture, the Extract-Transform-Load (ETL) module extracts data from a SAP database and feeds the Repository module, based on Elastic Search, with pre-processed data useful for the revision and decision processes. The OR module interacts with the ETL module just for the management of obsolete component reusing by harmonizing, as it will be shown in the rest of the paper, all the production, procurement and logistic activities. All data in the Repository, either coming from OR or directly from ETL, are mixed and fused on a Kibana Dashboard for visualization purposes.

In the field of industry informatics, the application of a novel data and processing framework to one of the most complex scenarios available in the fashion market is one of the main contributions of the proposed approach together with the novel OR model to maximize the potential revenue from reusing obsolete components.

This introduction continues with the description of a worldwide case study with real data and of ad hoc strategies within an Industry 4.0 scenario.

1.1. The worldwide case study

A real worldwide case study related to eyewear manufacturing is investigated in this section, focusing on embedding an optimal solution for obsolete component reusing within the existing framework. The case study was approached for a company that has an overall production of 93 millions of prescription glasses and sunglasses and counts many manufacturing facilities, distribution centres and a wide network of retail stores spread worldwide. Company hubs can be used for both the production of glasses and the storage of components and the orders of parts can be done from each hub using a local procurement network.

The cost of stocked and ordered components varies according to component's type and location. Transfer costs of raw materials have to be managed in order to enhance profits and to increase savings. The established management policy for the mainstream production consists of weekly scheduled transfers of materials between company's hubs. The transfer of components proposed in this work is done according to the scheduled transfers, amortising the fixed cost for a potential new cargo transfer.

Data used to solve this problem are complex, semi-structured and, if we consider a global company test case, big in term of number of records. The solution to be applied in a real scenario is supposed to be fast, optimal and able to assist actions and decisions in a worldwide and multi-user scenario. For these reasons we propose a modern data architecture in an industrial informatics scenario able to mix data analytics and OR tool.

In the following the words *product*, *finished good*, *glasses* and *item*, as well as *component*, *part* and *raw material* are interchangeable.

1.2. Challenges in fashion markets and industrial strategy

Fashion products follow trends that can be imposed or offered to customers and, in both cases, the forecast demand cannot be as expected due to trend variability or bad response to the products proposed. Since the products have a high turnover, some items go rapidly out of market, becoming out of fashion. All the components related to outmoded products are called obsolescences. The high demand variability can lead to an overstock of material giving two main drawbacks: first, stoked obsolescences increase the management costs and secondly they represent frozen assets that cannot be sold diversely, risking to be lost. A largely adopted strategy in the reusing of obsolescences is to produce outmoded products that will be sold in the *second market*. Indeed, the selling markets can be generally divided in two main branches: *first market* and *second/outlet market*. The former includes all the current products that follow the trend; such products are considered top sellers and are pushed by the company. The latter has all the out of fashion products, which companies sell at a discounted price with respect to the original list price. The use of secondary markets guarantees the reduction of storage costs, a potential increase in profits and the appreciation of obsolete components.

The *OR module* aims at maximizing the potential revenue at the net of (purchased or stocked) component costs and of transfer and manufacturing costs necessary for the production.

The paper is organized as follow. After a brief literature review in Section 2, Section 3 describes the software architecture, Section 4 presents the issue related to the reusing of obsolete components and the mathematical formulation of the problem. Section 5 describes the data formalism used in the tests performed and the results obtained. A deep analysis of the results is reported in Subsection 5.1. Conclusions and future works are presented in Section 6.

2. Literature Review

Mix production and resource management problems are widely faced in literature from different points of view. Warehouse management is strictly connected with storage and packing processes [3] as well as facility location and transportation management. The design of a distribution network is a crucial task that has to be taken into account during the design process. A comprehensive review of academics works for these problems can be found in [4].

On the other hand, big companies embed specific tools dedicated to resource handling into their management software. The logistics staff often can use a warehouse management system (WMS), a database application software, to improve the efficiency of warehouses ([5]), but in many case custom solution approaches are necessary to fit particular situations or specific requirements to keep stock levels under control ([6]).

In [7] warehousing systems are presented giving a description of several types of storage management and presenting a hierarchy for the decision problem encountered in setting up each variant of a warehousing system.

Due to the inherent complexity of production management, mathematical modelling techniques such as Integer Linear Programming (ILP) are widely used to solve many problems related to production planning, manufacturing [8] [9], furniture industry [10], automotive [11], plant locations [12] [13], team/crew management [14] and software architecture decision planning [15]. Mathematical programming is also useful as a merely modelling language to describe complex problems eventually solved by meta-heuristic algorithms: in [16] the authors model the aggregate production planning (APP) problem with multi-period, multi-product and multi-machine systems through a mixed integer linear program (MILP) and develop a genetic algorithm and a tabu search to solve it. They compare the results obtained by the two algorithms with those computed by LINGO solver and discuss the limits of the MILP approach, which is able to solve only small-sized instances. In [17] the authors studied the APP problem in the general and discrete versions, modelled it by ILP and proposed a modified particle swarm optimization algorithm. A decision support system is proposed in [18] where an End-to-End Customer Order Management System, composed by three integrated tools, supports real-time order management, considering limited shared resources and risk of missing orders.

According with the idea of ”reusing”, both [19] and [20] approach the production planning of industrial commodities considering the appreciation of discontinued item’s parts. In the former, the authors analyse the hybrid production system where new and remanufactured products are assembled at the same time.

Either by reusing parts of old products or by refurbishing them, the company improves his environment-friendly public image by enhancing his selling probability and respecting government for recycling. The model proposed considers different aspects like production capacity, durability of recycled used parts and competition between new and used products aiming at maximizing the overall profit. In the latter, a reverse supply chain (RSC) is designed to better exploits end-of-life vehicles (ELV). Conforming to the ELV classification, the authors propose a multi-product RSC modelled as a possibilist mixed-integer programming problem able to minimize the total cost of the RSC network.

A methodological framework for production and transportation is presented in [21]. The authors combine optimization and simulation techniques to increase profit and reduce CO_2, showing that random variability of demand plays an important role on production costs and freight performance. As in this paper, the authors identify the shipment plans and the transportation schedule according to BOM lists, different suppliers' prices and production/transportation costs. The production plan is also analysed in [22], where a multi-objective evolutionary algorithm is used to investigate robust order scheduling problems in the fashion industry. Also in this work, the uncertainty of the daily production quantity heavily influences the scheduling order.

In [23], the authors propose an MILP based heuristic able to optimize a two level supply chain with multiple suppliers and manufacturing plants aiming to minimize the total cost for the production necessary to satisfy customers demand.

The previously cited works, as well as others in the literature not reported here, study the production planning from different points of view and with various optimization techniques, but, at the best of the authors' knowledge, there are no works focusing on the reusing or appreciation of obsolescences as defined in this paper. Besides, none of the previously cited papers is based on a modern big data architecture able to mix data analytics and result optimization for supporting decision making and action in complex logistic and procurement systems.

3. The software architecture

3.1. System Architecture

The software system architecture here proposed is schematized in Fig. 1 and consists of the following modules:

- *ETL*, which feeds the *Repository* with data processed;
- *OR*, implementing and solving the optimization task;
- *Repository*, which stores information;
- *Dashboard*, for visualizing dynamic analytics and reports;
- *Decision Actuator* DSS, which chooses solutions and simulates their impact before implementing the activities.

Data are imported from a SAP platform, which provides the integration of information and processes, in addition to industry-specific functionality and scalability.

The *ETL* module is a sophisticate toolset for organising, manipulating and collecting data. This software component makes data more efficient, effective and reportable. *ETL* processes are fundamental being responsible for the extraction of data from heterogeneous sources, their transfer to the specific areas of the data warehouse where they will be processed, the data transformation and the computation of new values for obeying to the data warehouse structure to which they are targeted, the isolation and cleansing of problematic tuples to guarantee that database constraints and business rules are respected.

Most data intelligence techniques similar to the scenario described before require significant preprocessing of the voluminous raw data, which must be cleaned, filtered and organized into a usable format for querying. Often, this step is a one-time effort because the goal is to perform an offline analysis, rather than to provide ongoing support for interactive querying of live and growing online data. Consequently, researchers often opt to store the processed data in a well known RDBMS, such as MySQL or SQLite, much simpler to set up and easier to query. While this kind of approach is likely the best choice for some tasks, it is not well suited to the needs of Big Data analysis, which requires supporting much larger volumes of data, accommodating the real-time nature of incoming data and providing quick responses to queries. In a traditional RDBMS, large data require the creation of many indices to reduce the execution time of queries; at the same time the presence of indices greatly slows the process of data updating. Since neither of these choices is practical in presence of Big Data, it is worthwhile to consider what other approaches might work well in designing a repository. On the basis of our experience with Elasticsearch, an open source search engine that provides near real-time search and full-text search capability, as well as a RESTful API, we have used Elasticsearch to build a tool that collects data coming from an *ETL* process and is able to mix structured and unstructured data in a logistic and procurement scenario of a global brand. The main characteristics is the ability of Elasticsearch to mix different sources and to interact with both the *OR* module, described in the next session, and the *ETL* module (Fig. 1). The proposed system provides aggregated information about the process and a full set of APIs to bring back processed data in the production list or, in general, in the ERP. The improvement in response time was remarkable, so that it enabled users to interact with our analysis in real time. This effectively turned our proof-of-concept research tool into a practical industrial-strength *OR* and analytics tool.

The *Dashboard* module allows to review in a synthetic way both the warehouse status and the part of the analytics with the performance of the management. The data visualization system is based on Kibana [24], an open source data visualization plugin for Elasticsearch. It provides visualization capabilities on top of the content indexed on an Elasticsearch cluster. Users can create bars, lines and scatter plots or pie charts and maps on top of large volumes of data. The *Dashboard* displays a set of saved visualizations, such as the current size of the store, the projection of the cost of materials provided and the procurements programmed by the planner.

As it will be shown in section 5, the *OR* module offers a range of solutions, that can be pareto-optimal according to some parameters (as order cost, production, stock values used, etc.). The *Decision Actuator*, exploiting the solutions proposed by the *OR* module, allows to simulate how the adoption of each solution will change the situation of the warehouse. It also generates the corresponding production orders and the handling of components to be passed to the SAP database. In other words, this module shows a set of outputs and their related effects in terms of warehouse value used, order costs, production and other computed parameters. An example of data analysis is give in section 5.1.

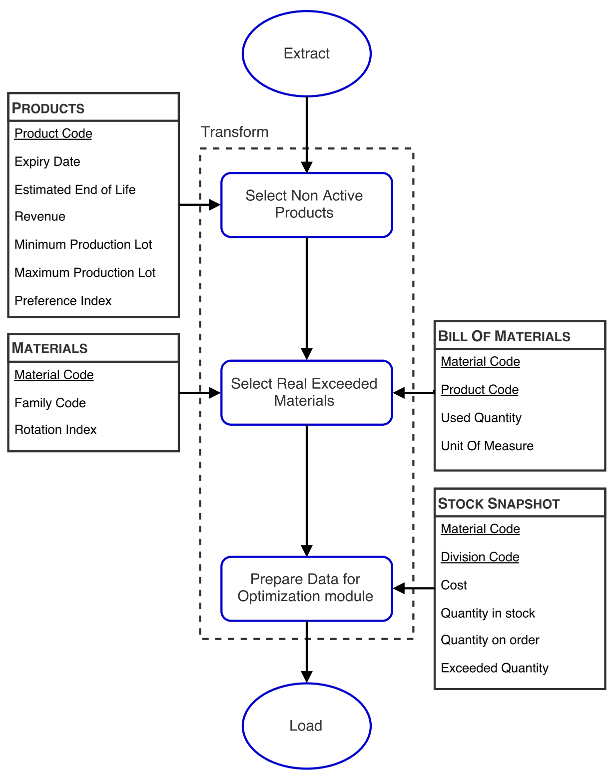

Figure 2: Example of an *ETL* process. The schema represents operations performed to filter surplus data, before loading input data to the *OR* module. Other extracted tables and fields unnecessary to complete these operations are not displayed.

3.2. Data Processing

The *ETL* module extracts data from the SAP database and transforms and processes them to build the input data for the optimization model. The *OR* module, described in details in Subsection 4.1, solves the mathematical model on the prepared instance and saves the output data.

The *ETL* module then loads results of *OR* module in the *Repository* to analyse the impact of optimization on the warehouse.

As an example, Figure 2 depicts the *ETL* process we implemented to identify the surpluses in company's warehouses, with the aim of surplus reduction by optimizing the reusing of products no longer active.

Initially, the data extracted from the SAP database by the "Extract" operation give the image of the warehouse, with all the available products and components and the active and non active products. Stocks levels are recorded for each component in every warehouse, giving the real state of the company's productivity power. Synchronization issues don't rise because the SAP system is able to provide real data of all the worldwide distributed warehouses which do not have high level variability due to their nature (obsolete components). Each extracted instance has real and accurate data.

In the "Transform" operation no more active products are identified by `Expiry Date` (exceeded this date orders for that product are not accepted) and `Estimated End Of Life` (date of production end). The input data prepared for the *OR* module are lists of:

- all reproducible products in each division;
- BOMs of reproducible products;
- the minimum and maximum lots, profit margins and the index of precedence for each reproducible product;
- surplus in each division for each usable material;
- production/purchase costs in each division for each usable material.

Finally, the "Load" operation is executed, by which the *ETL* module loads results of *OR* module in the *Repository* to analyse the impact of optimization on the warehouse.

4. The OR module

The previous section has exposed in details the company IT structure and the work done for integrating the new framework within the existing architecture. The *OR* module aims to propose a set of solutions to increase profits, reduce obsolete stocks and improve logistic/procurement management. This section presents the optimization problem that lies beneath the DSS, formalizing the problem definition and exposing the mathematical formulation used.

4.1. The obsolete part reusing problem

The problem of reusing obsolete parts can be formalized as follows. A set C of obsolete components are stored in a set D of worldwide production hubs. Let M be the set of outmoded glass types for the second market that can be produced with the obsolete components according to their bill-of-materials (BOM). In the interests of providing fuller information, it is worth mentioning that all the BOM of the problem are 1-layer BOM. Every hub is able to produce any type of glasses. The transfer of material between hubs is allowed as well as the purchase of new components. Procurement and storage costs depend on the hub chosen and component type: for each component $i \in C$ and hub $h \in D$, p_{ih} represents the cost for buying component i at the hub h, c_{ih} is the value of component i stocked in the hub h, and v_{ih} is 0 (for each h) if the component i is obsolete and corresponds to c_{ih} otherwise. Finally, the parameter g_{ih} indicates the number of components i stocked in the plant h. Since most of the stocked components are obsolete is supposed to have many parts already in the warehouses making useless any reference to safety stock levels. Furthermore, production hubs are surrounded by a network of providers that closely collaborate with the company according to a providing policy forecast of

3-6 months giving full support to company needs. Nevertheless, *second market* production is pretty small compared to the overall production (one twentieth of it) and scheduled in few events (6-7 in total) in the whole year. This means that the second market production can accomplished almost effortless.

Since the company has cargo flights that regularly move components among all production/storage hubs according to a weekly schedule, the fixed transportation cost for obsolete components can be neglected. In our approach, indeed, transportation costs are considered proportional to the cost m_{hk} for moving a unit of any component between any pair of hubs h and k.

For each BOM associated to a glass type $j \in M$, the parameters a_{ij} states the number of components $i \in C$ needed to assemble a unit of product j. The revenue for each manufactured glasses is expressed by parameter r_j, that is, the retail price the product will be sold. Products sold in the second market have a selling price that is ranged between 60% to 70% of the real retail price.

Maximum overall production of glasses as well as budget for orders are bounded, respectively, by parameters Q and H. The sizes of production lots and order stocks are defined either for production or for orders. Parameters q_{jh} and Q_{jh} define, respectively, the minimum and maximum quantity of model type j that can be produced at hub h, while b_{ih} is the minimum size for a lot of component i ordered/produced in hub h. All the above parameters are available for the *OR* module after the extraction and transformation processes performed by the *ETL* module. Parameters are summarized in the following list:

- M: set of items that can be produced;
- C: set of components listed in the BOMs related to items in M;
- D: set of hubs;
- a_{ij}: number of components $i \in C$ necessary to produce an item $j \in M$;
- g_{ih}: number of parts of component $i \in C$ that are stocked in the plant $h \in D$;

- c_{ih}: storage cost of component $i \in C$ stocked in the plant $h \in D$;
- p_{ih}: cost of component $i \in C$ ordered/produced in the plant $h \in D$;
- v_{ih}: value of component $i \in C$ stored in the plant $h \in D$; the value is 0 if component i is obsolete;
- r_j: revenue of the item $j \in M$;
- w_{jh}: revenue of the item $j \in M$ produced in plant $h \in D$;
- Q: maximum overall number of items that can be produced;
- q_{jh}: minimum size of a production lot of the item $j \in M$ produced in plant $h \in D$;
- Q_{jh}: maximum size of a production lot of the item $j \in M$ produced in plant $h \in D$;
- b_{ih}: minimum size of a lot of component $i \in C$ acquired/produced by the plant $h \in D$;
- H: budget availability for component purchasing or manufacturing;
- m_{hk}: cost for moving a component (whatever type) from plant/warehouse $h \in D$ to plant/warehouse $k \in D$;
- μ: *opportunity ratio* between the purchasing or manufacturing cost of new components and the value of obsolete parts reused.

The opportunity ratio μ limits the number of ordered components to a percentage of the stocked ones used for the production. The resulting order quantities will be more "rational" in the solution obtained because they are bounded by the quantity of stocked material used in the manufacturing process.
The proposed integer linear program (1)-(13) works on the following decision variables:

- x_{jh}: integer number of items of type $j \in M$ produced in plant $h \in D$;

- y_{jh}: binary variable that states if item $j \in M$ is produced or not in plant $h \in D$;
- z_{ihk}: integer number of components $i \in C$ ordered/produced in the plant $h \in D$ and used for production in plant $k \in D$;
- u_{ihk}: integer number of obsolete components $i \in C$ stored in plant $h \in D$ and used for production in plant $k \in D$;
- t_{ih}: binary variable that states if component $i \in C$ is produced/ordered in plant $h \in D$.

The objective function (1) maximizes the total potential revenue by taking into account the costs for purchasing and moving components between hubs and the value of the stocked components used. The set of constraints (2) bounds the number of components used for production to those purchased or available in each given warehouse. Constraint (3) limits the components used to the quantity actually stocked. The *opportunity* constraint (4) limits the value of purchased components to a percentage μ of the value of stocked materials used for the production. Overall production is bounded by constraint (5), while constraint (6) defines the minimum and maximum lot size. The budget for material purchasing is limited by constraint (7) and constraints (8) range the size of lot for components' orders to given minimum and maximum values.

$$\max \sum_{j \in M, h \in D} w_{jh} x_{jh} - \sum_{\substack{i \in C \\ h,k \in D}} (z_{ihk}(p_{ih} + m_{hk}) + u_{ihk}(v_{ih} + m_{hk})) \tag{1}$$

$$\sum_{j \in M} a_{ij} x_{jk} \leq \sum_{h \in D} (z_{ihk} + u_{ihk}) \quad \forall i \in C, \forall k \in D \tag{2}$$

$$\sum_{k \in D} u_{ihk} \leq g_{ih} \quad \forall i \in C, \forall h \in D \tag{3}$$

$$\mu \sum_{\substack{i\in C\\ h,k\in D}} c_{ih}u_{ihk} \geq \sum_{\substack{i\in C\\ h,k\in D}} p_{ih}z_{ihk} + \sum_{\substack{i\in C\\ h,k\in D}} m_{hk}(u_{ihk}+z_{ihk}) \tag{4}$$

$$\sum_{\substack{j\in M\\ k\in D}} x_{jk} \leq Q \tag{5}$$

$$y_{jk}q_{jk} \leq x_{jk} \leq y_{jk}Q_{jk} \qquad \forall j \in M, \forall k \in D \tag{6}$$

$$\sum_{\substack{i\in C\\ h,k\in D}} p_{ih}z_{ihk} \leq H \tag{7}$$

$$b_{ih}t_{ih} \leq \sum_{k\in D} z_{ihk} \leq \frac{H}{p_{ih}}t_{ih} \qquad \forall i \in C, \forall h \in D \tag{8}$$

$$z_{ihk} \quad \text{integer} \qquad \forall i \in C, \forall (h,k) \in D \times D \tag{9}$$

$$u_{ihk} \geq 0 \qquad \forall i \in C, \forall (h,k) \in D \times D \tag{10}$$

$$t_{ih} \quad \text{binary} \qquad \forall i \in C, \forall h \in D \tag{11}$$

$$x_{jh} \quad \text{integer} \qquad \forall j \in M, \forall h \in D \tag{12}$$

$$y_{jh} \quad \text{binary} \qquad \forall j \in M, \forall h \in D \tag{13}$$

For each type of outmoded glass, the solution of program (1)-(13) provides the production volume and location. Moreover, the stocked materials can be picked up from any warehouse and the order of new components is decided according to the price offered by each hub. The movement of materials takes into account the price of labour cost of the plant.

The problem is not plant-wise decomposable and can be easily connected to a knapsack problem, classifying it as *NP-hard*.

5. Experimental setup and Results

The mathematical model has been implemented in AMPL and solved by Cplex 12.5. Tests have been performed on a desktop pc, running Windows 7 Pro and equipped with an Intel Core i7 processor at 3.2 GHz and 6 GB of ram.

The company has provided a real scenario instance whose characteristics are summarized in Table 1. The original dataset has been modified for privacy

Table 1: Real scenario characteristics

# Models	# Components	# Hubs
957	3457	4

reasons and the public version can be downloaded from [25]. Components' cost and quantity have been provided as well as BOMs for each glasses. A guess about the transportation cost has been done for the movement of materials. The fixed transportation cost has not been considered due to the company policy, but a proportional cost is taken into account for each unit of material moved, according to labour cost of the country where the hub is located.

5.1. Data Analysis

To evaluate both theoretical and realistic scenarios, the three parameter sets reported in Table 2 have been considered.

The purpose of Configuration 1 is to test the model without any explicit limit and to evaluate the solution obtained for their viability and performance in a hypothetical scenario. As said earlier, the production for second market represents a slice of the overall production and an infinite budget or production quantity does not fit this situation. Configurations 2 and 3 represent feasible scenarios where the parameters are set according to company's guidelines. For each production phase, the quantity to produce or the budget for ordering components can vary according to the period of the year and these two configurations represent a viable framework the company works with.

Each configuration was run 10 times, varying the parameter μ from 0.1 to 1 with a step of 0.1. The maximum cpu time was set to 30 minutes for each run and the allowed gap between the best integer solution and the best bound was set to 10^{-5}.

With the first configuration, the solver reached the maximum cpu time allowed, giving solutions that, on average, have a relative gap of 3.963% with respect to the best bound found. In the Configuration 2, the solver performed better solving each instance in less than a minute and giving higher quality solutions with a gap of only 0.002%. In the last configuration, 9 instances needed all the 30 minute allowed and one instance was solved in less than five minutes. The average relative gap between best bound and best integer solution found is reported in Table 3 together with information about average problem size after CPLEX presolving.

Table 2: Configurations' parameters

	Q	q_{jk}[1]	Q_{jk}[1]	H	b_{ik}[1]
Configuration 1	∞	0	∞	∞	0
Configuration 2	100000	200	∞	∞	200
Configuration 3	100000	200	500	∞	200

[1] $\forall j \in M, \forall k \in D, \forall i \in C$

Table 3: Statistics for average solutions

	Avg.# vars	Avg.# of constraints	Relative gap
Configuration 1	58600	20900	3.963%
Configuration 2	84000	51000	0.002%
Configuration 3	36000	22000	5.381%

In the following, R indicates the potential revenue and P and C represent the cost of bought and used components, respectively. For sake of readability, W indicates the net profits, which are expressed by $W = R - P - C$. In the 10 runs with Configuration 1, CPLEX preprocessing reduced the ILP size to about 20900 constraints and 58600 variables. Table 4 summarizes the potential net profit W (expressed in millions of €) for each value of μ.

Figure 3 shows the ratio $\frac{R}{P+C}$ between potential revenue and costs faced for the production. This value represents an economical leverage or an investment indicator able to summarize the quality of the solution found. The dimension of spheres states the percentage value of the stocked components used (calculated with parameter c_{ik}). The ratio and the value of warehouse used grow according with the opportunity ratio. The value of the leverage, not considering the cost of stocked components, is always greater than 260, making the results in the first configuration very promising. However, a drawback of these solutions concerns their feasibility with respect to the production organization and, in particular, the compliance of the production lot sizes.

Table 4: Configuration 1 - Net profit for each run

μ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
W(M€)	4.3	12.9	23.8	39.5	63.2	96.2	132.4	156.8	214.2	267.4

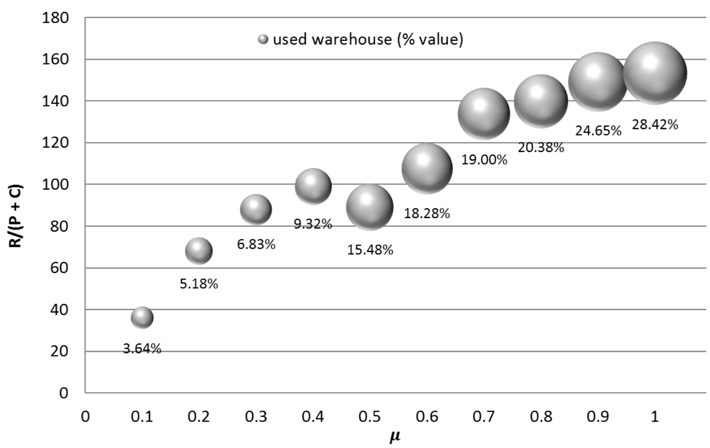

Figure 3: Configuration 1 - Revenue-Costs ratio and warehouse used

In Figure 4 and 5, in fact, it is represented in light grey the number of *small lots* (those with less than 200 units) ordered and produced with respect to the total purchased and manufactured lots. These small lots represent, on average, the 62% and 76% of ordered and produced lots for each value of μ. This aspect of the solutions would hinder the production of glasses and it could represent an infeasible scenario to be accomplished due to industrial constraints. Moreover, the production involves more than the 20% of the catalogue, making the production pretty complex to be managed.

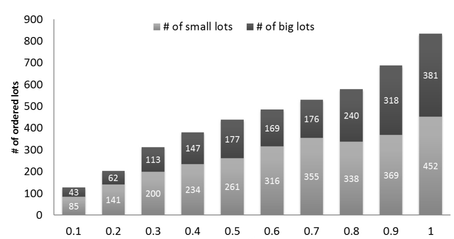

Figure 4: Configuration 1 - Small lots ordered

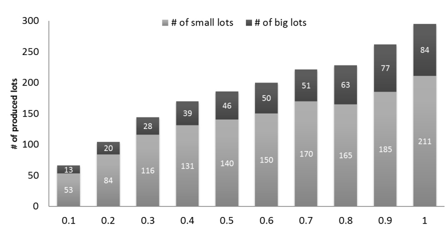

Figure 5: Configuration 1 - Small lots produced

In the 10 runs with Configuration 2 small lots are forbidden by the parameter setting and Figure 6 highlights the not linear variation of the ratio $\frac{R}{P+C}$, while Table 5 shows the net profit W for each value of μ.

Since the problem is strongly bounded in this configuration, the absolute value of W is much smaller. Except for an initial uncertainty, the trend of the leverage value is increasing as in Configuration 1, although the percentage of warehouse used decreases as the opportunity parameter increases.

Table 5: Configuration 2 - Net profit for each run

μ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
W(M€)	2.6	6.5	5.7	6.7	6.8	6.8	6.8	6.8	6.8	6.8

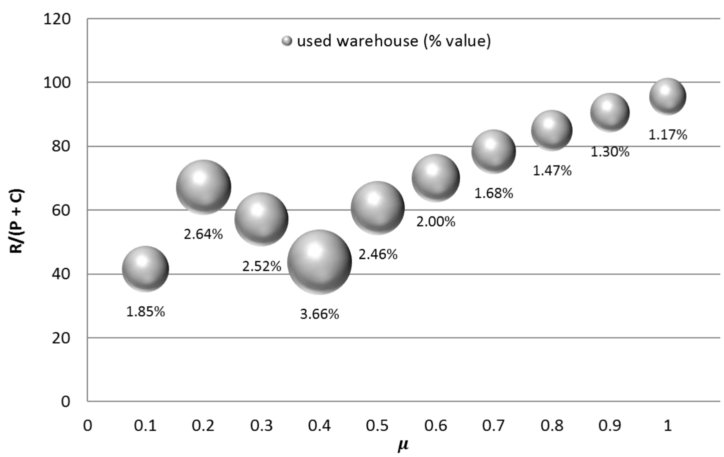

Figure 6: Configuration 2 - Revenue-Costs ratio and warehouse used

Table 6: Configuration 2 - Ordered and produced lots

μ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Lots ordered	25	33	24	52	22	20	16	10	10	10
Lots produced	11	17	15	21	13	12	12	10	9	9

Ordered and produced lots are much smaller than in the previous configuration, as shown in Table 6; the trends are roughly quadratic with peak points near the middle value of μ and reflect the percentage used of the available warehouse, as regulated by the opportunity constraint (4) of the mathematical formulation. With Configuration 2, the running times of the solver were reduced drastically, with an average of 325 seconds per run, and all the instances except one have been solved to optimality. Moreover and above all, the parameters' values represent a viable scenario, because they consider the manufacturing limits, such as lot sizes and overall manufacture volumes, usually taken into account in real productions. The solution obtained does not give a dominant strategy, because the opportunity ratio must be chosen according to a suitable trade-off. The graph and the table shown present several strategies and the best of them can be chosen according to warehouse or industrial requirements (reduction of warehouse volume) or emergency company policy (low budget for the purchase of new components).

In the 10 runs with Configuration 3, a limit on the production volume of each type of glass is added to follow the marketing indications and avoid the production of profitable but not popular glasses. Here, the behaviour of the leverage is completely different from the previous configurations (see Figure 7). In fact, the leverage decreases while the value of μ increases and a growing warehouse usage is registered. As in Configuration 2, the value of the opportunity parameter can be chosen by company needs or a suitable trade-off (see Table 7). In any case, the range of solutions is wide enough to have an overview of the strategies proposed.

A linear increase in the number of ordered and produced lots is experienced (see Figures 8 and 9) like in Configuration 1. Although the CPLEX preprocessor works better on the instances of Configuration 3 (resulting in formulations of smaller size), the constraints on the maximum number of glasses for each lot increase the problem complexity and, as a consequence, the solver is not able to close the gap within the prescribed cpu time (the average relative gap is of 5.381%).

Table 7: Configuration 3 - Net profit for each run

μ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
W(M€)	0.9	1.3	1.7	1.9	2.3	2.6	3.2	3.8	4.2	4.7

Transfers of components, either ordered or stocked, are summarized in Figure 10. For each configuration, the stocked material shifted among hubs is around

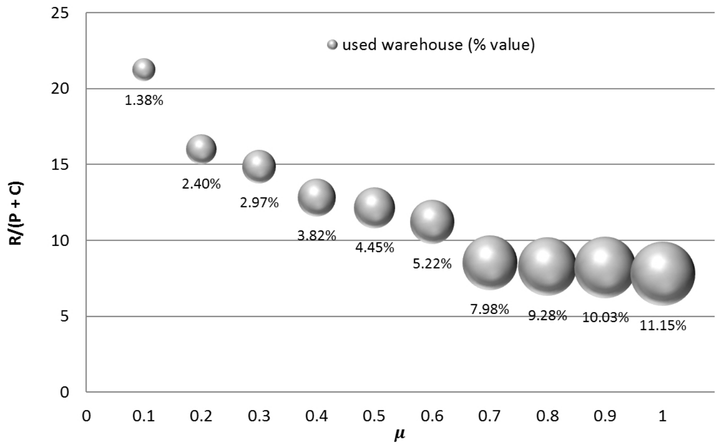

Figure 7: Configuration 3 - Revenue-Costs ratio and warehouse used

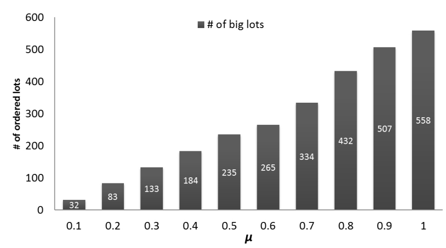

Figure 8: Configuration 3 - Small lots ordered

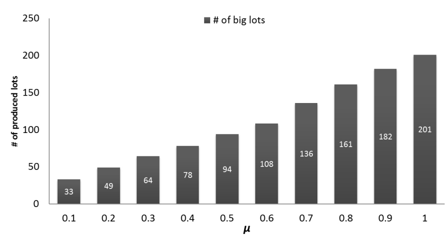

Figure 9: Configuration 3 - Small lots produced

the 30% of the components used, while the ordered parts are almost completely used in the same hub they are provided. This aspect highlights the importance of the re-usage of in-house materials even if it involves the transfer of a relevant part of the overall stocked components used.

6. Conclusions and future steps

In this paper we present a "Data Intelligence" framework for decision making activities in procurements, production, management and logistics. In particular, we embed in the existing software architecture a new *OR* module that provides optimal solutions to the problem of reusing obsolete components in fashion markets.

Data imported from the SAP database of the company that provided us

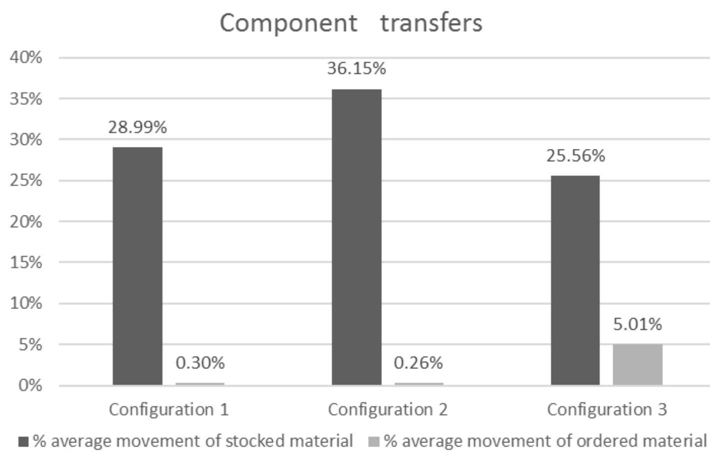

Figure 10: Transfers of components

with a real worldwide dataset are made more efficient, effective and reportable by the *ETL* module, which predisposes the input data for the *OR* module. The novel *OR* module collects a set of solutions that are shown through the Kibana *Dashboard*, which also allows to save the results to share or reload at a later time. Then through the REST interface of ElasticSearch the results of the *OR* module are loaded in the *Repository*. Finally, the *Decision Actuator* helps the production manager and the procurement planner in finding a good strategy. Through the solutions proposed by the *OR* module, the DSS allows to simulate how the adoption of those situations will change the situation of the warehouse and it also generates the corresponding production orders and movements of components to be passed to the SAP database.

In the *OR* module the optimization problem is formulated as an ILP, coded with AMPL and solved using the commercial solver CPLEX, inside a more general data architecture devoted to process and manage big data for this model.

In considering alternative solutions, let us point out how machine learning or deep learning approaches often does not reach the optimal solution and, above all, they are based on training data that are totally not applicable on this scenario.

The optimal solutions found by the *OR* module indicates:

- quantity and type of glasses to produce and plants where their production should take place;
- quantity and type of company-owned components to use for production and hubs from which these components are picked up;
- quantity and type of components to be purchased and locations where their purchasing should take place;
- transfers of stocked and purchased components between hubs.

The mathematical model has been tested on a real instance with 957 discontinued products, 3457 different components and 4 production hubs. Three configurations have been proposed where parameters' values are set according to real scenarios and we highlight pros and cons for each set of parameters.

Our analysis on real data from a worldwide scenario has shown variations of the trends with changes in the opportunity parameter μ. In each configuration, transfers of components mainly involve stocked parts, due to low transfer rates and negligible fixed transportation costs.

With Configuration 1 the high number of small lots represents a big issue with the possibility to incur in an infeasible solution due to industrial constraints.

Configuration 2 and 3 do not suggest explicit dominating solutions: in such scenarios the company can better exploit the *Dashboard* module to get the trading-off solutions that best fit the needs of the company. For these reasons it's better to have a range of good and heterogeneous strategies able to offer a range of suitable solutions instead of only one approach.

The approach proposed in this paper, based on a real worldwide scenario, results performing, effective and widely doable with a huge economic impact for the manufacturer that provided the case study (a glasses production leader company operating in 150 different countries). Furthermore, the mathematical model can be easily adapted to many other manufacturing processes and product types.

Future steps will be focused on the analysis of the scalability of the system to cover other areas of logistic and procurement, as well as on a deeper parameter evaluation, both over the proposed dashboard and the DSS, to further improve action planning.

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